Journal of Fuzzy Extension and Applications

www.journal-fea.com

J. Fuzzy. Ext. Appl. Vol. 6, No. 1 (2025) 94–108.

Paper Type: Research Paper

Recognition Principle for Course Allocations in Higher Institutions based on Intuitionistic Fuzzy Correlation Coefficient

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Citation:

Received: 13 March 2024 *Revised: 15 May 2024* *Accepted: 06 June 2024*	Ejegwa, P. A., Onyeke, I. Ch., & Adah, V. (2025). Recognition principle for course allocations in higher institutions based on intuitionistic fuzzy correlation coefficient. *Journal of fuzzy extension and applications, 6*(1), 94-108.

Abstract

To effectively evaluate relationships in uncertain environments, such as in decision-making, the idea of Intuitionistic Fuzzy Correlation Coefficient (IFCC) is employed. Several authors have provided many methods of IFCC, but their methods have some setbacks in correctness and accuracy. In this article, some novel methods of IFCC are developed that possess better exactness and reliability compared to the existing IFCC techniques. The new IFCC techniques possess high reliability and precision based on their mathematical formulations and the inclusion of all intuitionistic fuzzy parameters. The setbacks of the existing IFCC techniques are enumerated and verified with some numerical examples. Several of their properties are discussed in order to authenticate the novel IFCC techniques. More so, utilizing the new IFCC schemes in the issue of course allocations in higher institutions is discussed. Finally, the preeminence of the novel IFCC techniques is discussed in terms of precision and consistency with correlation principles by juxtaposing their effectiveness with other IFCC methods.

Keywords: Decision-making, Intuitionistic fuzzy correlation coefficient, Course allocation, Intuitionistic fuzzy set.

1 | Introduction

The higher institution admissions process based on academic preference is a herculean task full of imprecision due to competition and strict admission requirements. The admission officers are often confused 1) when

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https://doi.org/10.22105/jfea.2024.448400.1411

there are more qualified applicants vying for admission for a limited admission space, 2) when the evaluation parameters employed are imprecise and qualitative, and 3) when two or more applicants have an identical or related qualification. To resolve the imprecisions in the admission process, the approach of fuzzy reasoning (i.e. a model of human intelligence) is deployed into computer systems using fuzzy sets/logic [1]. Some studies have been carried out to tackle the imprecision of the admission process based on fuzzy reasoning [2–4]. But sometimes, fuzzy reasoning is handicapped due to the presence of hesitation.

Due to the problem with fuzzy sets, the idea of the Intuitionistic Fuzzy Set (IFS) [5] was constructed to enhance intuitionistic fuzzy reasoning, which is more promising and akin to human intelligence. While the fuzzy set considers the Membership Grade (MG) as a function described in $[0,1]$, the IFS is described by the MG, the Non-Membership Grade (NMG), and the Grade of Hesitation (GH), which are summed to unity. In addition, in the IFS setting, $\mathrm{MG} + \mathrm{NMG} \leq 1$.

Because of the relevance of IFS, many researchers have used the idea to discuss several pressing human problems. In [6], a distance measuring approach for IFSs was given and applied to the recognition of patterns. The concept of pattern recognition was buttressed using intuitionistic fuzzy reasoning based on information measures [7]. Similarly, IFSs have been used to model problems of decision-making [8]. IFS has been useful in healthcare, especially in disease diagnosis [9], [10]. In addition, everyday problems have been deliberated on using some intuitionistic fuzzy computation approaches [11], [12]. Several problems have been discussed using many uncertain approaches [13–19]. In recent times, the applications of IFSs have been addressed in medical emergencies [20], [21] and pattern recognition [22–24].

The theory of IFCC has been engaged in buttressing varied everyday problems. The correlation coefficient measures the resemblance between data, and the idea has been stretched to a fuzzy domain since many data are fuzzy and imprecise [25], [26]. IFCC was first studied in [27] and described within the interval [0,1] to enable the correlation coefficient to function in the intuitionistic fuzzy sphere. In [28], an approach for finding IFCC was developed akin to [26] but with a different model formulation in [29], [30], the IFCC method in [27] was modified differently by including GH.

To enhance reliable interpretation drawn from IFCC, Xu and Cai [31] modified the approach [28] by including GH. In [32], it was adjudged that the IFCC approaches in [28], [31] are defective. Hence, IFCC was developed to correct defectiveness and diagnose diseases. However, a novel approach to IFCC was developed in [33] based on a statistical viewpoint, i.e., described within the interval $[-1,1]$. Because the method in [34] does not consider GH, Park et al. [34] included the GH in the model in [33]. Following the approaches in [33], [34], some new methods of IFCC were developed and applied to diagnose diseases[35], [36].

Having reviewed the IFCC techniques, we are enthused to create new IFCC approaches for the following reasons:

I. The methods of IFCC in [28], [30], [33–36] are defective and infringe the condition of the correlation coefficient.

II. In [12], [27], [28], [32], [35], the GHs of the IFSs are not included in the IFCC methods, so the approaches

III. cannot be trusted to give reliable interpretations.

IV. The accuracy of the existing methods of IFCC is not encouraging.

In this study, we develop two IFCC methods that resolve the setbacks of the present IFCC schemes. The innovative IFCC techniques are conversed and applied to higher institution admission problems. The contributions of the article include:

I. Pinpoint the drawbacks in the present IFCC techniques based on numerical examples.

II. Develop new IFCC methods that resolve the drawbacks of the existing IFCC method and have better.

III. Validate the new IFCC methods using some theoretical results to showcase their agreement with the correlation coefficient properties.

IV. Discuss the use of the new IFCC techniques in selecting students for admission using intuitionistic fuzzy data.

The summary of the remaining portions of the article includes: Section 2 discusses IFSs and enumerates the present IFCC methods, Section 3 contains the new IFCC approaches, converses their properties and the setbacks of the present IFCC approaches, and computationally states the benefits of the new approaches over the obtainable methods, the use of the new approaches in the selection of students for admission purpose using intuitionistic fuzzy data has conversed in Section 4, and conclusion and some research suggestions are presented in Section 5.

2 | Preliminaries

Certain fundamental notions of IFSs are reviewed, and some existing techniques for scheming IFCC are given in this section.

2.1 | Intuitionistic Fuzzy Sets

The theory of fuzzy set was adapted to form a new set named IFS by including the non-membership degree. We designate $\mathfrak{A}$ as the non-empty set in this article.

Definition 1 ([5]). An IFS $\widetilde{\mathbb{M}}$ in $\mathfrak{A}$ is $\widetilde{\mathbb{M}} = \{\langle \mathfrak{A}_j, \xi_{\widetilde{\mathbb{M}}}(\mathfrak{A}_j), \eta_{\widetilde{\mathbb{M}}}(\mathfrak{A}_j)\rangle \mid \mathfrak{A}_j \in \mathfrak{A}\}$, where $\xi_{\widetilde{\mathbb{M}}}, \eta_{\widetilde{\mathbb{M}}}: \mathrm{U} \to [0,1]$ are functions signify MG and NMG for $\mathfrak{A}_j \in \mathfrak{A}$ to the set $\widetilde{\mathbb{M}}$, with $0 \leq \xi_{\widetilde{\mathbb{M}}}(\mathfrak{A}_j)+\eta_{\widetilde{\mathbb{M}}}(\mathfrak{A}_j) \leq 1$. The GH for IFS $\widetilde{\mathbb{M}}$ is given as $\varpi_{\widetilde{\mathbb{M}}}(\mathfrak{A}_j) = 1 - \xi_{\widetilde{\mathbb{M}}}(\mathfrak{A}_j) - \eta_{\widetilde{\mathbb{M}}}(\mathfrak{A}_j)$. For ease of presentation, we take $\left(\xi_{\widetilde{\mathbb{M}}}(\mathfrak{A}_j), \eta_{\widetilde{\mathbb{M}}}(\mathfrak{A}_j)\right)$ as the Intuitionistic Fuzzy Number (IFN), symbolized by $\widetilde{\mathbb{M}} = (\xi, \eta)$.

Now, the explanations of IFCC are given within $[0,1]$ and $[-1,1]$ as follows.

Definition 2 ([15]). For an IFSs $\widetilde{\mathbb{M}}_1$ and $\widetilde{\mathbb{M}}_2$ in $\mathfrak{A} = \{\mathfrak{A}_1, \mathfrak{A}_2, \dots, \mathfrak{A}_k\}$, the IFCC between $\widetilde{\mathbb{M}}_1$ and $\widetilde{\mathbb{M}}_2$ signified by $\Omega(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2)$, under $[0,1]$ is a function, $\Omega : \widetilde{\mathbb{M}}_1 \times \widetilde{\mathbb{M}}_2 \to [0,1]$ in which;

I. $\Omega(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = \Omega(\widetilde{\mathbb{M}}_2, \widetilde{\mathbb{M}}_1)$,

II. $\Omega(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) \in [0,1]$,

III. $\Omega(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = 1 \Leftrightarrow \widetilde{\mathbb{M}}_1 = \widetilde{\mathbb{M}}_2$.

A strong positive correlation concerning $\widetilde{\mathbb{M}}_1$ and $\widetilde{\mathbb{M}}_2$ is shown as $\Omega_*(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2)$ tends to 1, and the correlation is weak as $\Omega_*(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2)$ moves closer to 0. In addition, $\Omega_*(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = 1$ points to a perfect positive correlation and $\Omega_*(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = 0$ points to a zero correlation.

Definition 3 ([21]). For an IFSs $\widetilde{\mathbb{M}}_1$ and $\widetilde{\mathbb{M}}_2$ in $\mathfrak{A} = \{\mathfrak{A}_1, \mathfrak{A}_2, \dots, \mathfrak{A}_k\}$, the IFCC between $\widetilde{\mathbb{M}}_1$ and $\widetilde{\mathbb{M}}_2$ signified by $\Omega(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2)$, under $[-1,1]$ is a function, $\Omega : \widetilde{\mathbb{M}}_1 \times \widetilde{\mathbb{M}}_2 \to [-1,1]$ in which,

I. $\Omega(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = \Omega(\widetilde{\mathbb{M}}_2, \widetilde{\mathbb{M}}_1)$,

II. $\Omega(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) \in [-1,1]$,

III. $\Omega(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = 1 \Leftrightarrow \widetilde{\mathbb{M}}_1 = \widetilde{\mathbb{M}}_2$.

A strong positive correlation concerning $\widetilde{\mathbb{M}}_1$ and $\widetilde{\mathbb{M}}_2$ is shown as $\Omega_*(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2)$ moves closer to 1, and the correlation is weak as $\Omega_*(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2)$ tends to -1. In addition, $\Omega_*(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = 1$ points to a perfect positive and $\Omega_*(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = -1$ points to a perfect negative correlation.

2.1.1 | Existing IFCC methods

Here, a number of existing IFCC methods are enumerated. Given $\widetilde{\mathbb{M}}_1$ and $\widetilde{\mathbb{M}}_2$ as two random IFSs in $\mathfrak{A} = \{\mathfrak{A}_1, \mathfrak{A}_2, \dots, \mathfrak{A}_k\}$, then [26] presented the following IFCC scheme:

$$\Omega_1(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = \frac{\sum_{j=1}^{k}\left(\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}{\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \eta^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)}\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \eta^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}}. \tag{1}$$

According to Hung [32], we get

$$\Omega_2(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = \frac{1}{2}\left(, k_\xi(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) + k_\eta(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2)\right), \tag{2}$$

where

$$k_\xi(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = \frac{\sum_{j=1}^{k}\left[\left(\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) - \bar{\xi}_{\widetilde{\mathbb{M}}_1}\right)\left(\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) - \bar{\xi}_{\widetilde{\mathbb{M}}_2}\right)\right]}{\left[\sqrt{\sum_{j=1}^{k}\left(\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) - \bar{\xi}_{\widetilde{\mathbb{M}}_1}\right)^2}\sqrt{\sum_{j=1}^{k}\left(\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) - \bar{\xi}_{\widetilde{\mathbb{M}}_2}\right)^2}\right]}.$$

$$\bar{\xi}_{\widetilde{\mathbb{M}}_1} = \frac{\sum_{j=1}^{k}\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)}{k}, \quad \bar{\eta}_{\widetilde{\mathbb{M}}_1} = \frac{\sum_{j=1}^{k}\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)}{k},$$
$$\bar{\xi}_{\widetilde{\mathbb{M}}_2} = \frac{\sum_{j=1}^{k}\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)}{k}, \quad \bar{\eta}_{\widetilde{\mathbb{M}}_2} = \frac{\sum_{j=1}^{k}\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)}{k}.$$

According to Xu [28], we have

$$\Omega_3(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = \frac{1}{2k}\sum_{j=1}^{k}\left(\frac{\Delta\xi_{min} + \Delta\xi_{max}}{\Delta\xi_j + \Delta\xi_{max}} + \frac{\Delta\eta_{min} + \Delta\eta_{max}}{\Delta\eta_j + \Delta\eta_{max}}\right), \tag{3}$$

where

$$\Delta\xi_{min} = \min_j\left\{\left|\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) - \xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right|\right\}, \Delta\eta_{min} = \min_j\left\{\left|\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) - \eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right|\right\},$$

$$\Delta\xi_{max} = \max_j\left\{\left|\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) - \xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right|\right\}, \Delta\eta_{max} = \max_j\left\{\left|\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) - \eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right|\right\},$$

$$\Delta\xi_j = \left|\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) - \xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right|, \Delta\eta_j = \left|\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) - \eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right|.$$

According to Zeng and Li [29], we have

$$\Omega_4(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = \frac{C(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2)}{\sqrt{C(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_1)}\sqrt{C(\widetilde{\mathbb{M}}_2, \widetilde{\mathbb{M}}_2)}}, \tag{4}$$

where

$$C(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = \frac{\sum_{j=1}^{k}\left(\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \varpi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\varpi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}{k},$$

$$C(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_1) = \frac{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \eta^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \varpi^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)}{k},$$

$$C(\widetilde{\mathbb{M}}_2, \widetilde{\mathbb{M}}_2) = \frac{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \eta^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \varpi^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}{k}.$$

Xu et al. [30] presented two methods:

$$\Omega_5(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2) = \frac{\sum_{j=1}^{k}\left(\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\varpi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\varpi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}{\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)+\eta^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)+\varpi^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)}\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\eta^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\varpi^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}}. \quad (5)$$

$$\Omega_6(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2) = \frac{\sum_{j=1}^{k}\left(\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\varpi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\varpi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}{\max\left\{\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)+\eta^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)+\varpi^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)},\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\eta^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\varpi^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}\right\}} \quad (6)$$

According to Park et al. [34], we get

$$\Omega_7(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2) = \frac{1}{3}\left(k_\xi(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)+k_\eta(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)+k_\varpi(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)\right), \quad (7)$$

where

$$k_\xi(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2) = \frac{\sum_{j=1}^{k}\left[\left(\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\bar{\xi}_{\widetilde{\mathbb{M}}_1}\right)\left(\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)-\bar{\xi}_{\widetilde{\mathbb{M}}_2}\right)\right]}{\left[\sqrt{\sum_{j=1}^{k}\left(\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\bar{\xi}_{\widetilde{\mathbb{M}}_1}\right)^2}\sqrt{\sum_{j=1}^{k}\left(\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)-\bar{\xi}_{\widetilde{\mathbb{M}}_2}\right)^2}\right]},$$

$$k_\eta(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2) = \frac{\sum_{j=1}^{k}\left[\left(\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\bar{\eta}_{\widetilde{\mathbb{M}}_1}\right)\left(\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)-\bar{\eta}_{\widetilde{\mathbb{M}}_2}\right)\right]}{\left[\sqrt{\sum_{j=1}^{k}\left(\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\bar{\eta}_{\widetilde{\mathbb{M}}_1}\right)^2}\sqrt{\sum_{j=1}^{k}\left(\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)-\bar{\eta}_{\widetilde{\mathbb{M}}_2}\right)^2}\right]},$$

$$k_\varpi(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2) = \frac{\sum_{j=1}^{k}\left[\left(\varpi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\bar{\varpi}_{\widetilde{\mathbb{M}}_1}\right)\left(\varpi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)-\bar{\varpi}_{\widetilde{\mathbb{M}}_2}\right)\right]}{\left[\sqrt{\sum_{j=1}^{k}\left(\varpi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\bar{\varpi}_{\widetilde{\mathbb{M}}_1}\right)^2}\sqrt{\sum_{j=1}^{k}\left(\varpi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)-\bar{\varpi}_{\widetilde{\mathbb{M}}_2}\right)^2}\right]},$$

$$\bar{\xi}_{\widetilde{\mathbb{M}}_1} = \frac{\sum_{j=1}^{k}\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)}{k},\ \bar{\eta}_{\widetilde{\mathbb{M}}_1} = \frac{\sum_{j=1}^{k}\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)}{k},\ \bar{\varpi}_{\widetilde{\mathbb{M}}_1} = \frac{\sum_{j=1}^{k}\varpi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)}{k},$$

$$\bar{\xi}_{\widetilde{\mathbb{M}}_2} = \frac{\sum_{j=1}^{k}\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)}{k},\ \bar{\eta}_{\widetilde{\mathbb{M}}_2} = \frac{\sum_{j=1}^{k}\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)}{k},\ \bar{\varpi}_{\widetilde{\mathbb{M}}_2} = \frac{\sum_{j=1}^{k}\varpi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)}{k}.$$

According to Xu and Cai [31], we have

$$\Omega_8(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2) = \frac{1}{3k}\sum_{j=1}^{k}\left(\frac{\Delta\xi_{\min}+\Delta\xi_{\max}}{\Delta\xi_j+\Delta\xi_{\max}}+\frac{\Delta\eta_{\min}+\Delta\eta_{\max}}{\Delta\eta_j+\Delta\eta_{\max}}+\frac{\Delta\varpi_{\min}+\Delta\varpi_{\max}}{\Delta\varpi_j+\Delta\varpi_{\max}}\right), \quad (8)$$

Where

$$\Delta\xi_{\min} = \min_j\left\{\left|\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right|\right\},\ \Delta\eta_{\min} = \min_j\left\{\left|\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right|\right\},$$

$$\Delta\varpi_{\min} = \min_j\left\{\left|\varpi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\varpi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right|\right\},$$

$$\Delta\xi_{\max} = \max_j\left\{\left|\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right|\right\},\ \Delta\eta_{\max} = \max_j\left\{\left|\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right|\right\},$$

$$\Delta\varpi_{\max} = \max_j\left\{\left|\varpi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\varpi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right|\right\},$$

$$\Delta\xi_j = \left|\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right|,\quad \Delta\eta_j = \left|\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right|,\quad \Delta\varpi_j = \left|\varpi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\varpi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right|.$$

According to Liu et al. [35], we have

$$\Omega_9(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2) = \frac{C(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)}{\sqrt{C(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_1)}\sqrt{C(\widetilde{\mathbb{M}}_2,\widetilde{\mathbb{M}}_2)}}, \quad (9)$$

where

for $C(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)=\frac{\sum_{j=1}^{k}\Delta_j(\widetilde{\mathbb{M}}_1)\Delta_j(\widetilde{\mathbb{M}}_2)}{k-1}$, $C(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_1)=\frac{\sum_{j=1}^{k}\Delta_j^2(\widetilde{\mathbb{M}}_1)}{k-1}$, $C(\widetilde{\mathbb{M}}_2,\widetilde{\mathbb{M}}_2)=\frac{\sum_{j=1}^{k}\Delta_j^2(\widetilde{\mathbb{M}}_2)}{k-1}$,

$\Delta_j(\widetilde{\mathbb{M}}_1)=\left(\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\bar{\xi}_{\widetilde{\mathbb{M}}_1}\right)-\left(\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\bar{\eta}_{\widetilde{\mathbb{M}}_1}\right)$,

$\Delta_j(\widetilde{\mathbb{M}}_2)=\left(\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)-\bar{\xi}_{\widetilde{\mathbb{M}}_2}\right)-\left(\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)-\bar{\eta}_{\widetilde{\mathbb{M}}_2}\right)$,

$\bar{\xi}_{\widetilde{\mathbb{M}}_1}=\frac{\sum_{j=1}^{k}\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)}{k}$, $\bar{\eta}_{\widetilde{\mathbb{M}}_1}=\frac{\sum_{j=1}^{k}\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)}{k}$,

$\bar{\xi}_{\widetilde{\mathbb{M}}_2}=\frac{\sum_{j=1}^{k}\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)}{k}$, $\bar{\eta}_{\widetilde{\mathbb{M}}_2}=\frac{\sum_{j=1}^{k}\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)}{k}$.

According to Huang and Guo [32], we

$$\Omega_{10}(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)=\frac{1}{2k}\sum_{j=1}^{k}\left(\mu_j(1-\Delta\xi_j)+\nu_j(1-\Delta\eta_j)\right), \tag{10}$$

where

$\mu_j=\frac{c-\Delta\xi_j-\Delta\xi_{max}}{c-\Delta\xi_{min}-\Delta\xi_{max}}$, $\nu_j=\frac{c-\Delta\eta_j-\Delta\eta_{max}}{c-\Delta\eta_{min}-\Delta\eta_{max}}$, $c>2$,

$\Delta\xi_{min}=\min_j\{|\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)|\}$, $\Delta\eta_{min}=\min_j\{|\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)|\}$,

$\Delta\xi_{max}=\max_j\{|\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)|\}$, $\Delta\eta_{max}=\max_j\{|\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)|\}$,

$\Delta\xi_j=|\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)|$, $\Delta\eta_j=|\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)|$.

Finally, Thao et al. [36] presented the following method:

$$\Omega_{11}(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)=\frac{C(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)}{\sqrt{C(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_1)}\sqrt{C(\widetilde{\mathbb{M}}_2,\widetilde{\mathbb{M}}_2)}}, \tag{11}$$

where

$$C(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_1)=\frac{\sum_{j=1}^{k}\left[\left(\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\bar{\xi}_{\widetilde{\mathbb{M}}_1}\right)^2+\left(\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\bar{\eta}_{\widetilde{\mathbb{M}}_1}\right)^2\right]}{k-1},$$

$$C(\widetilde{\mathbb{M}}_2,\widetilde{\mathbb{M}}_2)=\frac{\sum_{j=1}^{k}\left[\left(\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)-\bar{\xi}_{\widetilde{\mathbb{M}}_2}\right)^2+\left(\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)-\bar{\eta}_{\widetilde{\mathbb{M}}_2}\right)^2\right]}{k-1},$$

$$C(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)=\frac{\sum_{j=1}^{k}\left[\left(\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\bar{\xi}_{\widetilde{\mathbb{M}}_1}\right)\left(\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)-\bar{\xi}_{\widetilde{\mathbb{M}}_2}\right)+\left(\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)-\bar{\eta}_{\widetilde{\mathbb{M}}_1}\right)\left(\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)-\bar{\eta}_{\widetilde{\mathbb{M}}_2}\right)\right]}{k-1},$$

$\bar{\xi}_{\widetilde{\mathbb{M}}_1}=\frac{\sum_{j=1}^{k}\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)}{k}$, $\bar{\eta}_{\widetilde{\mathbb{M}}_1}=\frac{\sum_{j=1}^{k}\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)}{k}$,

$\bar{\xi}_{\widetilde{\mathbb{M}}_2}=\frac{\sum_{j=1}^{k}\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)}{k}$, $\bar{\eta}_{\widetilde{\mathbb{M}}_2}=\frac{\sum_{j=1}^{k}\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)}{k}$.

3 | New IFCC Techniques

Having enumerated some existing IFCC approaches, it is natural to present the new IFCC techniques that resolve the limitations of the aforementioned methods. Given $\widetilde{\mathbb{M}}_1$ and $\widetilde{\mathbb{M}}_2$ as two random IFSs in $\mathfrak{A}=\{\mathfrak{A}_1,\mathfrak{A}_2,\dots,\mathfrak{A}_k\}$, then the new techniques for assessing the correlation coefficient concerning $\widetilde{\mathbb{M}}_1$ and $\widetilde{\mathbb{M}}_2$ are as follows:

$$\tilde{\Omega}_1(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = \frac{\sqrt{\sum_{j=1}^{k}\left(\xi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\xi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\eta_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\eta_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\varpi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\varpi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}}{\sqrt{\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)+\eta^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)+\varpi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)}\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\eta^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\varpi^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}}}. \tag{12}$$

$$\tilde{\Omega}_2(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = \frac{\sqrt{\sum_{j=1}^{k}\left(\xi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\xi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\eta_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\eta_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\varpi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\varpi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}}{\frac{\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)+\eta^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)+\varpi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)}+\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\eta^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\varpi^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}}{2}}. \tag{13}$$

Note that

$$\tilde{\Omega}_1(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = \frac{\sqrt{\sum_{j=1}^{k}\left(\xi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\xi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\eta_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\eta_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\varpi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\varpi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}}{\sqrt{\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)+\eta^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)+\varpi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)}\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\eta^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\varpi^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}}} = \sqrt[4]{\frac{\left(\sum_{j=1}^{k}\left(\xi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\xi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\eta_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\eta_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\varpi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\varpi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)\right)^2}{\sum_{j=1}^{k}\left(\xi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)+\eta^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)+\varpi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)\sum_{j=1}^{k}\left(\xi^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\eta^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\varpi^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}}.$$

3.1 | Verification Examples

Now, we express the limitations of the existing IFCC methods and show that the new IFCC methods are better than the existing methods.

Example 1. Suppose $\tilde{\mathbb{M}}_1 = \left(\frac{1}{3},\frac{1}{3}\right)$ and $\tilde{\mathbb{M}}_2 = \left(\frac{1}{4},\frac{1}{4}\right)$ are IFSs in $\mathfrak{A} = \{\mathfrak{A}_1\}$. Using new methods, we have $\tilde{\Omega}_1(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 0.971$ and $\tilde{\Omega}_2(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 0.9705$, respectively. However, the technique in [26] yields $\Omega_1(\tilde{\wp}_1,\tilde{\wp}_2) = 1$, though $\tilde{\wp}_1 \neq \tilde{\wp}_2$, which violates the condition of correlation. In addition, Ω_1 excludes the hesitation margins of $\tilde{\wp}_1$ and $\tilde{\wp}_2$, which can affect the precision of the result.

Example 2. Suppose $\tilde{\mathbb{M}}_1 = \left(\frac{1}{4},\frac{1}{4}\right),\left(\frac{1}{8},\frac{1}{8}\right)$ and $\tilde{\mathbb{M}}_2 = \left(\frac{1}{2},\frac{1}{2}\right),\left(\frac{1}{4},\frac{1}{4}\right)$ are IFSs in $\mathfrak{A} = \{\mathfrak{A}_1,\mathfrak{A}_2\}$. The methods in [32], [33] yield $\Omega_2(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = \Omega_7(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 1$ though $\tilde{\mathbb{M}}_1 \neq \tilde{\mathbb{M}}_2$, which violates the condition of correlation. Nonetheless, with the new methods, we get $\tilde{\Omega}_1(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 0.8641$ and $\tilde{\Omega}_2(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 0.8638$, respectively. In addition, Ω_2 excludes the hesitation margins of the IFSs, which can affect the result's precision.

Example 3. Suppose $\tilde{\mathbb{M}}_1 = \left(\frac{3}{10},\frac{3}{5}\right),\left(\frac{1}{2},\frac{3}{10}\right),\left(\frac{2}{5},\frac{1}{2}\right)$ and $\tilde{\mathbb{M}}_2 = \left(\frac{1}{10},\frac{1}{10}\right),(1,0),(0,1)$ are IFSs in $\mathfrak{A} = \{\mathfrak{A}_1,\mathfrak{A}_2,\mathfrak{A}_3\}$. Using the methods in [28], [29] we have $\Omega_4(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 0.6391$, $\Omega_5(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 0.6391$ and $\Omega_6(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 0.7174$, respectively. If $\tilde{\mathbb{M}}_1 = \tilde{\mathbb{M}}_2$, then $\Omega_4(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 1$, $\Omega_5(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 1$ and $\Omega_6(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 1.1225$, that is, Ω_6 infringes the condition of correlation. Using the new methods, we get $\tilde{\Omega}_1(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 0.7994$ and $\tilde{\Omega}_2(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 0.7857$, which is better than the outcomes from the methods in [28], [29]. If $\tilde{\mathbb{M}}_1 = \tilde{\mathbb{M}}_2$, then $\tilde{\Omega}_1(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = \tilde{\Omega}_2(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 1$, in agreement with the condition of correlation, contrasting Ω_6.

Example 4. If $\tilde{\mathbb{M}}_1 = \left(\frac{2}{5},\frac{3}{10}\right),\left(\frac{3}{10},\frac{1}{5}\right)$ and $\tilde{\mathbb{M}}_2 = \left(\frac{3}{10},\frac{1}{5}\right),\left(\frac{1}{5},\frac{1}{10}\right)$ are IFSs in $\mathfrak{A} = \{\mathfrak{A}_1,\mathfrak{A}_2\}$. Using the methods in [27], [30], we have $\Omega_3(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 1$ and $\Omega_8(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 1$ though $\tilde{\mathbb{M}}_1 \neq \tilde{\mathbb{M}}_2$, which infringes on the conditions of IFCC. Again, if $\tilde{\mathbb{M}}_1 = \tilde{\mathbb{M}}_2$, we get $\Omega_3(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = \Omega_8(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = \infty$ which is undefined and also violates the condition of IFCC. Using the scheme in [31], we have $\Omega_{10}(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 0.9$, which is realistic compared to the methods in [27], [30], Again, if $\tilde{\mathbb{M}}_1 = \tilde{\mathbb{M}}_2$, we have $\Omega_{10}(\tilde{\mathbb{M}}_1,\tilde{\mathbb{M}}_2) = 1$, which is far better than the unrealistic

result given by Ω_3 and Ω_8. Using the new methods, we get $\widetilde{\Omega}_1(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = 0.9663$ and $\widetilde{\Omega}_2(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = 0.9645$, which are better and more realistic than the results yielded by the methods in [27], [30], [31]. If $\widetilde{\mathbb{M}}_1 = \widetilde{\mathbb{M}}_2$, then $\widetilde{\Omega}_1(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = \widetilde{\Omega}_2(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = 1$, in agreement with the condition of correlation, unlike Ω_3 and Ω_8. The results of Ω_3 and Ω_{10} cannot be reliable because the hesitation margins are not included.

Example 5. Suppose $\widetilde{\mathbb{M}}_1 = \left(\frac{1}{3}, \frac{1}{3}\right), \left(\frac{1}{2}, \frac{1}{2}\right)$ and $\widetilde{\mathbb{M}}_2 = \left(\frac{1}{4}, \frac{1}{4}\right), \left(\frac{1}{2}, \frac{1}{3}\right)$ are IFSs in $\mathfrak{A} = \{\mathfrak{A}_1, \mathfrak{A}_2\}$. Then, by using the new techniques, we have to get $\widetilde{\Omega}_1(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = 0.9696$ and $\widetilde{\Omega}_2(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = 0.7737$, respectively. Using the method in [34], we get $\Omega_9(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = \infty$, which is unrealistic and violates the condition of IFCC. In addition, the result from Ω_9 cannot be reliable as the hesitation margins are not included.

Example 6. Suppose $\widetilde{\mathbb{M}}_1 = \left(\frac{1}{2}, \frac{1}{2}\right), \left(\frac{1}{2}, \frac{1}{2}\right)$ and $\widetilde{\mathbb{M}}_2 = \left(\frac{1}{3}, \frac{1}{3}\right), \left(\frac{1}{3}, \frac{1}{3}\right)$ are IFSs in $\mathfrak{A} = \{\mathfrak{A}_1, \mathfrak{A}_2\}$. Employing the method in [35], the correlation coefficient is impractical and violates the condition of correlation (i.e., $\Omega_{11}(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = \infty$). Using the new approaches, the correlation coefficients are 0.9036 and 0.899, respectively. rly, the result of Ω_{11} cannot be dependable because the hesitation margins are omitted.

Therefore, the two new IFCC methods are more reliable and give more accurate results than those under IFSs. Hence, the two newly developed methods are applied to determine students' course allocation into a higher institution.

Some results are presented to authenticate the new methods of calculating IFCC, which are as follows.

Theorem 1. Let $\widetilde{\mathbb{M}}_1$ and $\widetilde{\mathbb{M}}_2$ be IFSs in $\mathfrak{A}$, then the new IFCC methods satisfy the following:

I. $\widetilde{\Omega}_1(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = \widetilde{\Omega}_1(\widetilde{\mathbb{M}}_2, \widetilde{\mathbb{M}}_1)$,

II. $\widetilde{\Omega}_2(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = \widetilde{\Omega}_2(\widetilde{\mathbb{M}}_2, \widetilde{\mathbb{M}}_1)$.

Proof: recall that

$$\widetilde{\Omega}_1(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = \frac{\sqrt{\sum_{j=1}^{k}\left(\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \varpi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\varpi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}}{\sqrt{\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \eta^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \varpi^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)}\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \eta^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \varpi^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}}}.$$

Then it follows thus:

$$\widetilde{\Omega}_1(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = \frac{\sqrt{\sum_{j=1}^{k}\left(\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \varpi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\varpi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}}{\sqrt{\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \eta^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \varpi^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)}\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \eta^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \varpi^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}}}$$

$$= \frac{\sqrt{\sum_{j=1}^{k}\left(\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \varpi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\varpi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)}}{\sqrt{\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \eta^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \varpi^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \eta^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \varpi^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)}}}$$

$$= \widetilde{\Omega}_1(\widetilde{\mathbb{M}}_2, \widetilde{\mathbb{M}}_1),$$

which verifies (I). The evidence for (II) is similar.

Theorem 2. Suppose $\widetilde{\mathbb{M}}_1$ and $\widetilde{\mathbb{M}}_2$ be IFSs in $\mathfrak{A}$, then $\widetilde{\Omega}_1(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2)$ and $\widetilde{\Omega}_2(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2)$ satisfies the following:

I. $\widetilde{\Omega}_1(\widetilde{\mathbb{M}}_1, \widetilde{\mathbb{M}}_2) = 1$ iff $\widetilde{\mathbb{M}}_1 = \widetilde{\mathbb{M}}_2$,

II. $\tilde{\Omega}_2(\tilde{\mathbb{M}}_1, \tilde{\mathbb{M}}_2) = 1$ iff $\tilde{\mathbb{M}}_1 = \tilde{\mathbb{M}}_2$.

Proof: suppose $\tilde{\Omega}_1(\tilde{\mathbb{M}}_1, \tilde{\mathbb{M}}_2) = 1$, then we have

$$\sqrt{\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \eta^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \varpi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)}\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \eta^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \varpi^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}} =$$

$$\sqrt{\sum_{j=1}^{k}\left(\xi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\xi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \eta_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\eta_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \varpi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\varpi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)} \Rightarrow$$

$$\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \eta^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \varpi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)}\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \eta^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \varpi^2_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)} =$$
$$\sum_{j=1}^{k}\left(\xi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\xi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \eta_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\eta_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \varpi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\varpi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right) \Rightarrow$$

$$\sum_{j=1}^{k}\left(\xi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \eta^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \varpi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)\sum_{j=1}^{k}\left(\xi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \eta^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \varpi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right) =$$
$$\left(\sum_{j=1}^{k}\left(\xi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\xi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \eta_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\eta_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \varpi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\varpi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)\right)^2 \Rightarrow$$

$$\sum_{j=1}^{n}\left(\xi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \eta^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \varpi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)\left(\xi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \eta^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \varpi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)$$

$$= \sum_{j=1}^{n}\left(\xi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\xi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \eta_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\eta_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j) + \varpi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\varpi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)^2.$$

Which infers that $\tilde{\mathbb{M}}_1 = \tilde{\mathbb{M}}_2$.

On the contrary, assume $\tilde{\mathbb{M}}_1 = \tilde{\mathbb{M}}_2$, then we have

$$\tilde{\Omega}_1(\tilde{\mathbb{M}}_1, \tilde{\mathbb{M}}_2) = \frac{\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \eta^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \varpi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)}}{\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \eta^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) + \varpi^2_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)}} = 1.$$

Hence, (I) is verified. The proof of (II) is equivalent.

Theorem 3. Suppose $\tilde{\Omega}_1(\tilde{\mathbb{M}}_1, \tilde{\mathbb{M}}_2)$ and $\tilde{\Omega}_2(\tilde{\mathbb{M}}_1, \tilde{\mathbb{M}}_2)$ are IFCCs for $\tilde{\mathbb{M}}_1$ and $\tilde{\mathbb{M}}_2$ in $\mathfrak{A}$, then $\tilde{\Omega}_1(\tilde{\mathbb{M}}_1, \tilde{\mathbb{M}}_2)$, $\tilde{\Omega}_2(\tilde{\mathbb{M}}_1, \tilde{\mathbb{M}}_2) \in [0,1]$.

Proof: the proof is complete if we show that $0 \leq \tilde{\Omega}_1(\tilde{\mathbb{M}}_1, \tilde{\mathbb{M}}_2) \leq 1$ and $0 \leq \tilde{\Omega}_2(\tilde{\mathbb{M}}_1, \tilde{\mathbb{M}}_2) \leq 1$, respectively. Certainly, $\tilde{\Omega}_1(\tilde{\mathbb{M}}_1, \tilde{\mathbb{M}}_2) \geq 0$ and $\tilde{\Omega}_2(\tilde{\mathbb{M}}_1, \tilde{\mathbb{M}}_2) \geq 0$, which completes the first aspect. Next, we show that $\tilde{\Omega}_1(\tilde{\mathbb{M}}_1, \tilde{\mathbb{M}}_2) \leq 1$ and $\tilde{\Omega}_2(\tilde{\mathbb{M}}_1, \tilde{\mathbb{M}}_2) \leq 1$. Assume that

$\sum_{j=1}^{k}\xi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) = \alpha, \sum_{j=1}^{k}\xi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j) = \beta,$

$\sum_{j=1}^{k}\eta_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) = \gamma, \sum_{j=1}^{k}\eta_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j) = \delta,$

$\sum_{j=1}^{k}\varpi_{\tilde{\mathbb{M}}_1}(\mathfrak{A}_j) = \varepsilon, \sum_{j=1}^{n}\varpi_{\tilde{\mathbb{M}}_2}(\mathfrak{A}_j) = \epsilon.$

Then,

$$\widetilde{\Omega}_1(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)$$

$$=\frac{\sqrt{\sum_{j=1}^{k}\left(\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\varpi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\varpi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}}{\sqrt{\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)+\eta^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)+\varpi^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)}\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\eta^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\varpi^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}}}$$

$$=\frac{\sqrt{\alpha\beta+\gamma\delta+\varepsilon\epsilon}}{\sqrt{\sqrt{\alpha^2+\gamma^2+\varepsilon^2}\sqrt{\beta^2+\delta^2+\epsilon^2}}}.$$

And so,

$$\widetilde{\Omega}_1^2(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)-1=\frac{\alpha\beta+\gamma\delta+\varepsilon\epsilon}{\sqrt{\alpha^2+\gamma^2+\varepsilon^2}\sqrt{\beta^2+\delta^2+\epsilon^2}}-1$$

$$=\frac{\alpha\beta+\gamma\delta+\varepsilon\epsilon-\left(\sqrt{\alpha^2+\gamma^2+\varepsilon^2}\sqrt{\beta^2+\delta^2+\epsilon^2}\right)}{\sqrt{\alpha^2+\gamma^2+\varepsilon^2}\sqrt{\beta^2+\delta^2+\epsilon^2}}$$

$$=-\frac{\left(\sqrt{\alpha^2+\gamma^2+\varepsilon^2}\sqrt{\beta^2+\delta^2+\epsilon^2}-(\alpha\beta+\gamma\delta+\varepsilon\epsilon)\right)}{\sqrt{\alpha^2+\gamma^2+\varepsilon^2}\sqrt{\beta^2+\delta^2+\epsilon^2}}\leq 0.$$

Hence, $\widetilde{\Omega}_1^2(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)-1\leq 0$. Thus, $\widetilde{\Omega}_1(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)\leq 1$.

Similarly,

$$\widetilde{\Omega}_2(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)$$

$$=\frac{\sqrt{\sum_{j=1}^{k}\left(\xi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\xi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\eta_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\eta_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\varpi_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\varpi_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}}{\text{Average}\left\{\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)+\eta^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)+\varpi^2_{\widetilde{\mathbb{M}}_1}(\mathfrak{A}_j)\right)},\sqrt{\sum_{j=1}^{k}\left(\xi^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\eta^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)+\varpi^2_{\widetilde{\mathbb{M}}_2}(\mathfrak{A}_j)\right)}\right\}}$$

$$=\frac{\sqrt{\alpha\beta+\gamma\delta+\varepsilon\epsilon\mathfrak{f}}}{\text{Average}\left\{\sqrt{\alpha^2+\gamma^2+\varepsilon^2},\sqrt{\beta^2+\delta^2+\epsilon^2}\right\}}.$$

Hence,

$$\widetilde{\Omega}_2^2(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)=\frac{\alpha\beta+\gamma\delta+\varepsilon\epsilon}{\left(\frac{\sqrt{\alpha^2+\gamma^2+\varepsilon^2}+\sqrt{\beta^2+\delta^2+\epsilon^2}}{2}\right)^2}$$

$$=\frac{4(\alpha\beta+\gamma\delta+\varepsilon\epsilon\mathfrak{f})}{\left(\sqrt{\alpha^2+\gamma^2+\varepsilon^2}+\sqrt{\beta^2+\delta^2+\epsilon^2}\right)^2}.$$

Then,

$$\widetilde{\Omega}_2^2(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)-1=\frac{4(\alpha\beta+\gamma\delta+\varepsilon\epsilon)}{\left(\sqrt{\alpha^2+\gamma^2+\varepsilon^2}+\sqrt{\beta^2+\delta^2+\epsilon^2}\right)^2}-1,$$

$$=\frac{4(\alpha\beta+\gamma\delta+\varepsilon\epsilon)-\left(\sqrt{\alpha^2+\gamma^2+\varepsilon^2}+\sqrt{\beta^2+\delta^2+\epsilon^2}\right)^2}{\left(\sqrt{\alpha^2+\gamma^2+\varepsilon^2}+\sqrt{\beta^2+\delta^2+\epsilon^2}\right)^2}=-\frac{\left(\sqrt{\alpha^2+\gamma^2+\varepsilon^2}+\sqrt{\beta^2+\delta^2+\epsilon^2}\right)^2-4(\alpha\beta+\gamma\delta+\varepsilon\epsilon)}{\left(\sqrt{\alpha^2+\gamma^2+\varepsilon^2}+\sqrt{\beta^2+\delta^2+\epsilon^2}\right)^2}\leq 0.$$

Thus, $\widetilde{\Omega}_2^2(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)-1\leq 0$, and so, $\widetilde{\Omega}_2(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)\leq 1$. Hence, $\widetilde{\Omega}_1(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2),\widetilde{\Omega}_2(\widetilde{\mathbb{M}}_1,\widetilde{\mathbb{M}}_2)\in[0,1]$.

4 | Application in Higher Institution Course Allocations

The section discusses how to allocate courses to students in higher institutions based on the new methods of IFCC. This application is conceivable because of uncertainties and imprecision in the course allocation process. Suppose there are k students symbolized by IFSs $\mathfrak{W}_1, \mathfrak{W}_2, \dots, \mathfrak{W}_k$, who are evaluated in relevant subjects $\alpha, \beta, \gamma, \delta, \varepsilon, \epsilon$, to determine their course allocations in a specific college. The subjects are the prerequisite for the allocation of the courses $\mathfrak{Y}_1, \mathfrak{Y}_2, \dots, \mathfrak{Y}_l$. The value of the correlation coefficient

$$\tilde{\Omega}(\mathfrak{W}_k, \mathfrak{Y}_l) = \max \begin{pmatrix} \tilde{\Omega}(\mathfrak{W}_1, \mathfrak{Y}_1) & \cdots & \tilde{\Omega}(\mathfrak{W}_1, \mathfrak{Y}_l) \\ \vdots & \ddots & \vdots \\ \tilde{\Omega}(\mathfrak{W}_k, \mathfrak{Y}_1) & \cdots & \tilde{\Omega}(\mathfrak{W}_k, \mathfrak{Y}_l) \end{pmatrix}, \tag{14}$$

Decide which course is the best fit for the students to study.

4.1 | Application Examples

Assume three students are applying to study medical courses where there is limited space in a faculty. The available courses in the faculty include pharmacy, nursing, anatomy, physiology, and midwifery, represented by $\mathfrak{Y}_1$, $\mathfrak{Y}_2$, $\mathfrak{Y}_3$, $\mathfrak{Y}_4$, and $\mathfrak{Y}_5$. The faculty has a principle of admitting students using their academic performance in an entrance assessment. The subjects' requirements to study any of the courses within the faculty are English language, Mathematics, Biology, Physics, Chemistry, and Health Science, represented by $\alpha, \beta, \gamma, \delta, \varepsilon$, and ϵ. The students are to sit for an examination in the enumerated subjects to determine their fitness to study any of the medical courses. The student's performance after the examination is presented as intuitionistic fuzzy data in *Table 1* (θ_1: Students ⟶ Subject Requirements).

Table 1. Students' performance.

θ_1	α	β	γ	δ	ε	ϵ
$\mathfrak{M}_1$	(0.6, 0.3)	(0.5, 0.4)	(0.6, 0.3)	(0.5, 0.3)	(0.5, 0.5)	(0.6, 0.2)
$\mathfrak{W}_2$	(0.5, 0.3)	(0.6, 0.3)	(0.5, 0.3)	(0.4, 0.5)	(0.7, 0.2)	(0.7, 0.3)
$\mathfrak{W}_3$	(0.7, 0.2)	(0.7, 0.1)	(0.6, 0.4)	(0.5, 0.4)	(0.4, 0.5)	(0.6, 0.4)

The grade of membership is the mark scored (or supposed to be scored) by a student, and the grade of non-membership is the mark allotted to the questions a student failed (or is supposed to fail). The faculty outlines the expected performance of the applicants to study the courses within the faculty concerning the enumerated subjects, presented as intuitionistic fuzzy data in *Table 2* (θ_2: subject requirements ⟶ courses).

Table 2. Faculty requirement scores.

θ_2	$\mathfrak{Y}_1$	$\mathfrak{Y}_2$	$\mathfrak{Y}_3$	$\mathfrak{Y}_4$	$\mathfrak{Y}_5$
α	(0.7, 0.2)	(0.9, 0.1)	(0.6, 0.3)	(0.8, 0.2)	(0.8, 0.15)
β	(0.8, 0.1)	(0.8, 0.2)	(0.5, 0.2)	(0.7, 0.2)	(0.8,0.1)
γ	(0.4, 0.3)	(0.7, 0.1)	(0.5, 0.3)	(0.7, 0.25)	(0.79, 0.2)
δ	(0.5, 0.4)	(0.6, 0.2)	(0.6, 0.2)	(0.6, 0.2)	(0.6, 0.3)
ε	(0.5, 0.3)	(0.6, 0.2)	(0.6, 0.3)	(0.7, 0.2)	(0.6, 0.2)
ϵ	(0.4, 0.3)	(0.8, 0.1)	(0.5, 0.2)	(0.6, 0.4)	(0.8, 0.05)

By applying *Eqs. (12)* and *(13)* after the computation of the hesitation margins using the information in *Tables 1* and 2, the suitable courses to be studied by each student are determined. See *Table 3* for the outcomes.

Table 3. Student and courses.

$\mathfrak{M}/\mathfrak{Y}$	$\mathfrak{Y}_1$	$\mathfrak{Y}_2$	$\mathfrak{Y}_3$	$\mathfrak{Y}_4$	$\mathfrak{Y}_5$
$\mathfrak{M}_1$	0.9579	0.9593	0.9807	0.9688	0.9619
	0.9579	0.9567	0.9805	0.9675	0.9594
$\mathfrak{M}_2$	0.9607	0.9555	0.9638	0.9693	0.9601
	0.9606	0.9535	0.9635	0.9685	0.9582
$\mathfrak{M}_3$	0.9682	0.9552	0.9625	0.9750	0.9664
	0.9679	0.9541	0.9616	0.9747	0.9654

A careful study of *Table 3*, we see that based on the performances of the students during the entrance examination, student $\mathfrak{M}_1$ is qualified to study anatomy, student $\mathfrak{M}_2$ is qualified to study physiology and student $\mathfrak{M}_3$ is qualified also to study physiology. The results of the two new methods yield the same interpretation, and they are approximately equivalent. This study explicates course allocations based on the recognition principle via correlation coefficient, and we recommend this approach be adopted in practical instances.

4.2 | Comparative Analysis

Now, we showcase the reasons for developing the new methods of IFCC by juxtaposing their outputs with the outputs of the methods of IFCC discussed in [27–29], [31–35]. These methods were employed to find the correlation coefficient between the students and the courses of study in *Table 1* and *Table 2*, respectively. The correlation coefficient outputs are contained in *Table 4*.

From the comparative outcomes in *Table 4*, it is apparent that the newly developed methods of IFCC are more accurate and give the most reliable results. The methods in [28, 30, 33–36] are defectives in Examples 1–6. In addition, some of the methods of IFCC, like the approaches in [12], [27], [28], [32], [35], exclude the impact of the GH, so their outputs cannot be trusted to give appropriate interpretations. For the avoidance of doubt, the methods in [33–35] show negative correlation coefficient values because the methods were developed from a statistics perspective described within $[-1,1]$, whereas the new techniques and the methods in [26–31] are defined based on the operating system of IFSs, in the interval $[0,1]$. Above all, the newly developed methods of IFCC provide a huge improvement on the existing approaches of IFCC using a tri-parametric approach defined within [0,1].

5 | Conclusion

This article has studied correlation coefficients based on intuitionistic fuzzy data because of the importance of the subject in practical decision-making. We explored some obtainable IFCCs and pinpointed their drawbacks, which suggested their inability to handle the decision-making process reliably. Meanwhile, in the article, we developed two new IFCC methods, which were verified to outweigh the existing techniques by yielding reasonable results and interpretation reliability. After authenticating the new IFCC methods via some theoretical results, the methods were used to discuss the allocation of courses to university applicants based on the recognition principle.

From the comparative analysis provided in *Table 4*, it is evident that the newly developed IFCC methods are more accurate and give the most reliable results. The new IFCC techniques could be applied to multiple decision-making attributes and extended to other uncertain environments. In addition, the IFCC methods could be used to discuss optimization techniques with application in the planning of production and distribution in supply chain organizations using intuitionistic fuzzy t-sets [14].

Table 4. Results for comparison.

Ω	$(\mathfrak{M}_1, \mathfrak{Y}_1)$	$(\mathfrak{M}_1, \mathfrak{Y}_2)$	$(\mathfrak{M}_1, \mathfrak{Y}_3$	$(\mathfrak{M}_1, \mathfrak{Y}_4)$	$(\mathfrak{M}_1, \mathfrak{Y}_5)$	$(\mathfrak{M}_1, \mathfrak{Y}_6)$
Ω_1	0.9237	0.9320	0.9305	0.9751	0.9486	0.9344
Ω_2	0.5800	−0.2917	0.6551	0.0101	−0.2212	0.4778
Ω_3	0.8750	0.7222	0.8056	0.7708	0.7986	0.7903
Ω_4	0.9052	0.9176	0.9203	0.9617	0.9385	0.9253
Ω_5	0.9052	0.9176	0.9203	0.9617	0.9385	0.9253
Ω_6	1.4764	1.4966	1.5010	1.5206	1.5306	1.5091
Ω_7	0.1580	−0.1794	0.4217	0.2048	−0.1183	0.2512
Ω_8	0.8472	0.7315	0.7870	0.7500	0.7616	0.7616
Ω_9	0.6466	−0.3093	0.4319	−0.2148	−0.0864	0.5163
Ω_{10}	0.8028	0.9313	0.8590	0.9531	0.8926	0.8725
Ω_{11}	0.4638	−0.2498	0.5149	0.1104	−0.3631	0.3965
$\tilde{\Omega}_1$	0.9514	0.9579	0.9593	0.9807	0.9688	0.9619
$\tilde{\Omega}_2$	0.9450	0.9579	0.9567	0.9805	0.9675	0.9594
	$(\mathfrak{M}_2, \mathfrak{Y}_1)$	$(\mathfrak{M}_2, \mathfrak{Y}_2)$	$(\mathfrak{M}_2, \mathfrak{Y}_3)$	$(\mathfrak{M}_2, \mathfrak{Y}_4)$	$(\mathfrak{M}_2, \mathfrak{Y}_5)$	$(\mathfrak{M}_2, \mathfrak{Y}_6)$
Ω_1	0.9240	0.9418	0.9227	0.9565	0.9511	0.9350
Ω_2	0.3319	0.1795	0.1383	−0.4293	−0.0895	0.3304
Ω_3	0.8646	0.7569	0.7639	0.7292	0.7153	0.8153
Ω_4	0.9091	0.9229	0.9130	0.9289	0.9396	0.9218
Ω_5	0.9091	0.9229	0.9130	0.9289	0.9396	0.9218
Ω_6	1.5103	1.5108	1.5168	1.4647	1.5610	1.5314
Ω_7	0.1641	0.0446	0.0772	−0.4842	−0.0888	−0.0296
Ω_8	0.8125	0.7269	0.7593	0.7176	0.7060	0.8194
Ω_9	0.3305	0.1317	0.0939	−0.4575	−0.2299	0.4371
Ω_{10}	0.8280	0.9090	0.8803	0.9463	0.9367	0.8625
Ω_{11}	0.2814	0.0881	0.1125	−0.4138	−0.0875	0.2924
$\tilde{\Omega}_1$	0.9535	0.9607	0.9555	0.9638	0.9693	0.9601
$\tilde{\Omega}_2$	0.9480	0.9606	0.9535	0.9635	0.9685	0.9582
	$(\mathfrak{M}_3, \mathfrak{Y}_1)$	$(\mathfrak{M}_3, \mathfrak{Y}_2)$	$(\mathfrak{M}_3, \mathfrak{Y}_3)$	$(\mathfrak{M}_3, \mathfrak{Y}_4)$	$(\mathfrak{M}_3, \mathfrak{Y}_5)$	$(\mathfrak{M}_3, \mathfrak{Y}_6)$
Ω_1	0.9249	0.9736	0.9279	0.9554	0.9550	0.9393
Ω_2	0.6007	0.7151	0.4473	−0.1130	0.3465	0.6479
Ω_3	0.8472	0.7083	0.8681	0.8542	0.6875	0.8045
Ω_4	0.9202	0.9373	0.9124	0.9264	0.9507	0.9339
Ω_5	0.9202	0.9373	0.9124	0.9264	0.9507	0.9339
Ω_6	1.5832	1.5345	1.5697	1.4647	1.6356	1.6067
Ω_7	0.6291	0.1915	0.1331	−0.0753	0.3770	0.4862
Ω_8	0.8148	0.7130	0.8565	0.8009	0.7222	0.7789
Ω_9	0.5736	0.8292	0.4361	−0.1222	0.8841	0.6764
Ω_{10}	0.8264	0.9603	0.8406	0.8785	0.9614	0.8882
Ω_{11}	0.5825	0.6578	0.5000	−0.0677	0.3341	0.6229
$\tilde{\Omega}_1$	0.9593	0.9682	0.9552	0.9625	0.9750	0.9664
$\tilde{\Omega}_2$	0.9554	0.9679	0.9541	0.9616	0.9747	0.9654

Acknowledgments

The authors are indebted to the reviewers for their valuable suggestions and supportive comments towards enriching the paper.

Authors' Contributions

P. A. Ejegwa: conceptualization of the problem; formulation of the problem; Writing—original draft. I. C. Onyeke and V. Adah: Methodology; Software; Validation; Data curation. All authors have read and agreed to publish the manuscript.

Funding

There is no funding for this research.

Data Availability

The data used for the study is contained in the manuscript.

Conflicts of Interest

This work has no conflict of interest.

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